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Analyzing Brand Positioning and Brand Image of Smartphone Brands in Indonesia by Mining Online Review

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Abstract

A strong brand image and brand positioning are necessary to grow and lead market share, particularly for the smartphone market in Indonesia due to the intense rivalry caused by the huge smartphone market size in Indonesia. This study uses text mining to evaluate online expert reviews to identify the brand positioning and image of the existing smartphone brands and series in Indonesia. The lexicon-based approach text mining, LIWC tool are used in the analysis. The result from LIWC was then processed using principal component analysis and clustering to map and classify smartphone brands and series. The result show that Apple and Samsung set their self apart from 4 other brands thanks to their distinctive proposition. The analysis on smartphone series shows that 7 out of 24 series from 6 smartphone brands have their own segment. All Apple series have their own segments. For Samsung, Samsung Galaxy S and Galaxy Z have their own segment compared to other Samsung series. Vivo Y are the only series from non-Samsung Android brand that have its own segment.

Keywords: *brand image, brand positioning, text mining, smartphone.*

1. Introduction

Smartphone functions are not only limited to communication needs but also provide various needs in one hand. The effectiveness and ease of use of smartphones in everyday life is the main reason most people have smartphones, especially in Indonesia. Indonesia's Ministry of Communication and Informatics stated that Indonesia is the country with the fourth largest smartphone users in the world. Indonesia Central Agency on Statistics stated that the percentage of the Indonesian population who own smartphones has positive trends and reaches more than 66% of the population

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which is equivalent to more than 181 million people. The smartphone market in Indonesia grew by 11.5% in Q1 2022 which was achieved after the economic recovery that started to occur in the second half of 2021 [11]. Indonesia is one of the countries with the most significant smartphone growth after China and India which makes a lot of smartphone brands enter the Indonesian market [32].

On the other hand, the development of the internet helps consumers to obtain actual information about a brand through reviews on various online platforms. User can easily submit opinion about products by using the online platform. That conveniences make users can provide reviews on smartphone usage according to the experience felt by each user more quickly and efficiently. Consumers can provide more effective and efficient reviews to communicate with companies anytime and anywhere through online reviews. This freedom of opinion provides an opportunity for many users to honestly share their experiences when using the product. On the other hand, expert review also became prevalent with the development of the internet. Expert could easily upload their review due to major success of internet portal [4]. Today, consumers are not only looking for quantity in product reviews but are also looking for the quality of information shared in online reviews [40]. Currently, consumers are faced with an abundance of reviews so consumers will interpret these reviews as brand messages and turn them into brand images in their minds [33]. When consumers are faced with various reviews of a product, most of them use the more reliable source as their reference before purchasing a product [42]. Consumers also feel that reviewers who have experience reviewing a product generate more helpful reviews for them [2].

Online reviews could act as a basis for determining brand image. In the case of an action, a brand image will be actively created in the minds of consumers. Brand image can influence consumer buying behavior which in this case acts as a reaction [33]. Companies get the opportunity to deepen information about their consumer preferences and find out their brand image and brand positioning through reviews provided by consumers. Companies must understand how consumers perceive and categorize existing products. From this, companies can make the position their products by differentiating the value of their product. Brand positioning is an important starting point in building strong consumer awareness among competitors and gaining a competitive advantage [7].

The qualitative nature of review that contain unstructured text data has made it difficult to analyze with conventional quantitative methods [10]. However, the development of technology such as the emergence of high-speed processing computer has supported the discovery of contemporary approach to extract more insightful finding such as text mining approach [29]. Text mining technique application becoming more popular in the recent year due to the abundance of qualitative and unstructured textual data. Various text mining method could be used to explore online reviews [25]. The approach used for exploring reviews usually classified into machine learning algorithms and Lexicon-based methods [8]. Machine learning approach perform slightly better than lexicon-based method but lexicon-based method also gain popularity in the recent year as the method are quicker and easier to apply and could be used when we have limited resources [18].

One of popular lexicon-based method to extract information from reviews is Linguistic Inquiry and Word Count (LIWC) [30]. LIWC is an easy tool to implement because it already has a ready-made dictionary, has psychological meaning, and have stable performance [18]. This is because LIWC has high convergent emotional validity. It can be seen from the transparency of LIWC in processing data to detect the meaning of various feelings in words related to focus of attention, social relationships, emotionality, and thinking style. LIWC has been widely used in the field of psychological marketing [26]. Brand image is related with not only physical attributes but also psychological attributes [35]. LIWC could be used to explore brand image based on psychological benefit of brand. However, most of previous research use machine learning based text mining which explore brand image based on physical attributes of the brand [15, 21, 23, 28, 34]. Research conducted by [3] which analyzes brand positioning and image using LIWC tool is the basic motivation for conducting this research.

Many studies which analyze brand position and brand image have been conducted by using user reviews as database for analysis, including research conducted by [3] which became the basic motivation of this research. However, user reviews have shortcoming that is the possibility of user bias in influencing the content of review quite high [4]. On the other hand, there are also expert reviews generate more in-depth information about the product and unbiased evaluation of a product [4]. Expert reviews and tend to be more objective without taking sides. Expert reviews generate more trusted evaluation as the content is less likely affected by reviewer bias than user reviews. Other than that, most of potential customer who want to purchase product tend to trust expert reviews as the basis to choose product because the reviewer and source credibility and integrity [41]. Expert reviews also have significant effect on the costumer purchase intention and decision [2]. Based on that motivation, we use expert reviews as database to analyze brand position and image in this research.

This research focuses on 6 smartphone brands that have the highest market share in Indonesia. The smartphone Brands that have the highest market share in Indonesia are Oppo with a market share of 21.00%, Samsung with a market share of 20.5%, Xiaomi with a market share of 18.5%, Vivo with a market share of 14.4%, Apple with a market share of 10.6%, and Realme with a market share of 7.8% [37]. This research will process data in the form of expert review articles obtained from several websites. Review articles obtained from various websites processed using LIWC tools, a lexicon-based text mining method. The result of LIWC tool analyzed and processed to determine the brand positioning and brand image of 6 smartphone brands in Indonesia. It is hoped that this research can provide information to related smartphone brand companies regarding brand image and brand positioning which can be used to formulate marketing strategies for smartphone brands in Indonesia.

2. Context Explanation

2.1. Smartphone

In today's life, mobile phones are called smartphones. Smartphones currently work as a medium of communication for various social circles. The urgency of buying a smartphone in society is heavily influenced by the drive for needs and prestige. The smartphone itself has two terms that act as an identity to differentiate and classify them. The first term is the smartphone brand. Brand is a distinctive name and/or symbol that aims to identify the seller's goods or services and differentiate these goods and services from its competitors [1]. The second term is the smartphone series. Each type of smartphone usually has different features, shapes, and prices. It is also undeniable that each different series or type of smartphone has a different target consumer.

2.2. Brand Image and Brand Positioning

Brand image is one of the important things that companies need to focus on. Brand image can influence consumers' decision to buy or not to buy the product. Brand image is a description of consumer associations and beliefs about certain brands [39]. The consumer always remembers the image attached to each brand. That beliefs perceive consumers how they view the product from each brand. On the other hand, brand positioning is one of the marketing strategies by offering a specific target segment with products that have features that fit with the targeted segment. The key to brand positioning is that the company must be able to recognize the characteristics and uniqueness of its product. Brand positioning is the position of a brand compared to its competitors in the minds of customers, prospects, and other stakeholders [14]. Brand positioning itself is one of the strategies to improve the company's brand image. If implemented properly, brand image and brand positioning will make consumers see a brand according to what the companies want.

2.3. Product Review

Product review is the evaluation of product experience in the form of text data [12]. There are two types of reviews: user reviews and expert reviews. Both types of review have quite obvious differences which are explained as follows:

- User Review

User reviews are feedback or opinions given by consumers after buying or trying products from a certain brand. User reviews can reduce uncertainty in the development process and have a positive effect on product development [20]. Potential customers or product users tend to think that information obtained from online user reviews about the products they are interested in is more accurate and reliable than official information from companies, either through official websites, brochures, advertisements and other forms [19]. In user reviews, user tend to be biased in delivering their reviews because they are only based on personal views and experiences. In addition, most user reviews are laymen who do not know in-depth about smartphones so that the results of the reviews are less in-depth.

- Expert Review

Expert reviews are review posted by expert evaluators, someone who have deep knowledge about certain products. Expert review usually tends to provide a more in-depth and detailed review without taking sides. Expert reviews tend to have high integrity as expert reviewer always tried to be evaluate the products objectively [4]. Expert reviews tend to be trusted by user who search information about the product rather than user review [41]. Expert reviews also more likely to influence purchase intention and purchase decision [2].

2.4. Text Mining

Text mining is a method of analyzing text into information that can be used for certain reasons. The data used in text mining is a text that has no pattern and uses natural language or grammar used by humans. Through text mining, this non-patterned text will be converted into structured data and more easily understood by certain parties. Before being analyzed, the text needs to be carried out in the initial stages so that it can be processed further. Text mining is a variation of data mining that seeks to find interesting patterns from a large set of textual data [24]. Text mining can be used for various forms of documents such as reviews, comments, feedback, articles, social media comments, and any other forms. The main objective of text mining could be separated into three parts: extracting and identifying word, extracting main topics discussed in the text, and extracting and identifying the relationship between words [8]. There are several techniques could be used in text mining but we can classify them into 2 types: machine learning algorithms and lexicon-based method [8]. Machine learning algorithms use supervised learning to analyze the text whereas lexicon-based method use established list of word dictionary to analyze the text [25]. Although machine learning approach generate a slightly better result, lexicon-based approach could be used easily [18].

3. Data Collection

This study used secondary data in the form of expert review articles published from several Indonesian-based websites. There are several criteria to choose the expert review articles:

- The review articles use Bahasa Indonesia
- Have at least 250 words
- The content consists of the explanation of smartphone features and smartphone usage experience
- The review articles explain smartphone series which are still being sold on the brand's official website in Indonesia as of December 2022

The total data collected amounted to 324 review articles which discuss 6 brands and 24 series with a minimum number of 40s reviews for each brand and 10 reviews for each series. There are 54 different websites included in this research. The details of collected article review are accessible on https://bit.ly/smartphonereviewdataset.Table 1 shows the top 10 websites with the highest number of review articles used in this research.

Table 1. Website with Top 10 Number of Review Articles.

Website Name	Total Review Article
gizmologi.id	50
gadgetren.com	38
carisinyal.com	28
jagatreview.com	18
detik.com	14
yangcanggih.com	14
tekno.kompas.com	11
hybrid.co.id	9
review1st.com	9
telset.id	9

4. Data Analysis

4.1. Text Mining using LIWC

A total of 324 reviews translated to English using google translate as automatic translation tool. Each review database then processed using Linguistic Inquiry and Word Count (LIWC) tools based on the LIWC-22 English Dictionary. The output of LIWC tool exhibit the word weighting of each review article based on the 117 variables determined by LIWC. These variables are grouped into 4 categories, namely Summary Variables, Linguistic Dimensions, Psychological Processes, and Expanded Dictionary. In this study, 41 variables used based on their relevance to the brand image and brand positioning. The chosen variables chosen including analytic, authentic, tone, achieve, tone negative, tone positive, emotion, emotion positive, emotion negative, emotion anxious, emotion anger, emotion sad, prosocial, money, need, want, acquire, lack, fulfill, reward, fatigue, risk, drives, affiliation, power, affect, social behavior, polite, conflict, moral, communication, lifestyle, leisure, mental, allure, curiosity, attention, perception, visual, auditory, and feeling. PIVOT table then generated to average 41 variables based on brands and series. LIWC result for brands and series is included in Appendix A.

4.2. Factor Establishment

As there are many variables included from LIWC output, we need to establish several factors to reduce the dimension of variables. The establishment of factor was using principal component analysis (PCA) approach.

- Factor Establishment for Brands

At this stage, it can be known the number of PCs that can be used through the variance formed. The main requirement for the number of PCs that can be used is that the eigenvalue score must more than 1 because the eigenvalue is useful for expressing how much diversity can be formed. This study used 4 PCs that meet the eigenvalue requirement more than 1. The 4 PCs extracted have been able to carry out 92.7% of data variation which is quite good.

Each PC labeled according to the correlation and with its constituent variables. The detail of each PC for brands shown in Appendix B.1. PC 1 represents 'user experience' because it places a lot of emphasis on variables related to perception, emotion, and social. PC 2 represents 'pride' as a symbol of pride in having a product from that brand which can be seen from the variables related to power, achievement, and mentality. PC 3 represents 'assurance & quality' which can be seen from the variable emotion anxious, desire, and risk. Then PC 4 which represents 'inadequate' as a symbol that there is something that needs to be fixed as a combination of 3 variables namely negative emotion, acquire, and fatigue.

- Factor Establishment for Series

Similar to PCA for brands, the PCA for series resulted 4 PCs being formed as the result of fulfilling the eigenvalue requirement more than 1. 4 PCs for series represented 56% of data variations, which was quite good because they represented more than half of data variations. The detail of each PC for series shown in Appendix B.2. From PCA results, PC 1 emphasizing variables related to perceptions and emotions, so PC 1 is considered to represent 'user experience'. PC 2 has many variables that are negative and related to deficiencies, so PC 2 can be judged to represent 'product imperfection'. Furthermore, PC 3 has variables related to anxiety, needs, and risks so can be assumed that PC 3 can represent 'assurance & quality'. PC 4 has variables related to social treatment, desire, and communication. It can be concluded that PC 4 represents 'consumer need'.

4.3. Perceptual Maps

This stage uses a proximity matrix which functions as a determinant of the distance between one object and another based on standardized variables, where the proximity matrix can help determine the perceptual map that will be formed. The proximity matrix table used is a dissimilarities matrix which means that the higher the value generated between one object and another, the higher the level of dissimilarity of the object.

- Perceptual Map for Brands

From the perceptual map shown in Figure 1a, Samsung and Apple are far apart from each other, which indicates that the level of dissimilarity between the two is quite high compared to other smartphone brands. Meanwhile, Samsung has a close position with Xiaomi, which indicates the level of similarity between the two is quite similar. Apart from that, it can also be seen that Apple and Samsung both occupy the different outermost side in the same axis. This means that Apple and Samsung both have quite a differentiating value for the reviewers compared to other brands in at least one attribute where the other brands being located in middle of those 2.

- Perceptual Map for Series

In the perceptual map for series shown in Figure 1b, most of smartphone series tend to gather in the middle. The series of Apple products tend to stay away from most of other series. All of Apple series located in the outermost side in the map. This result strengthens the evidence that Apple products are indeed different from other brands based on the result of perceptual map for brands. From Figure 1b, we also know that each Apple series have quite a distance with each other, meaning that each different series for Apple have a visible difference. From Figure 1b we also know that Vivo Y series and Samsung Galaxy Z have position that are closer to the series of apple products than android products. Samsung Galaxy Z series have closer position with iPhone SE. This is contrary to the results of the perceptual map for brands which show that Samsung and Apple are far apart. Vivo Y series have closer position with iPhone 14 series. This means that Vivo Y series have quite differentiation with the other series of Vivo that gather in the middle part of map.

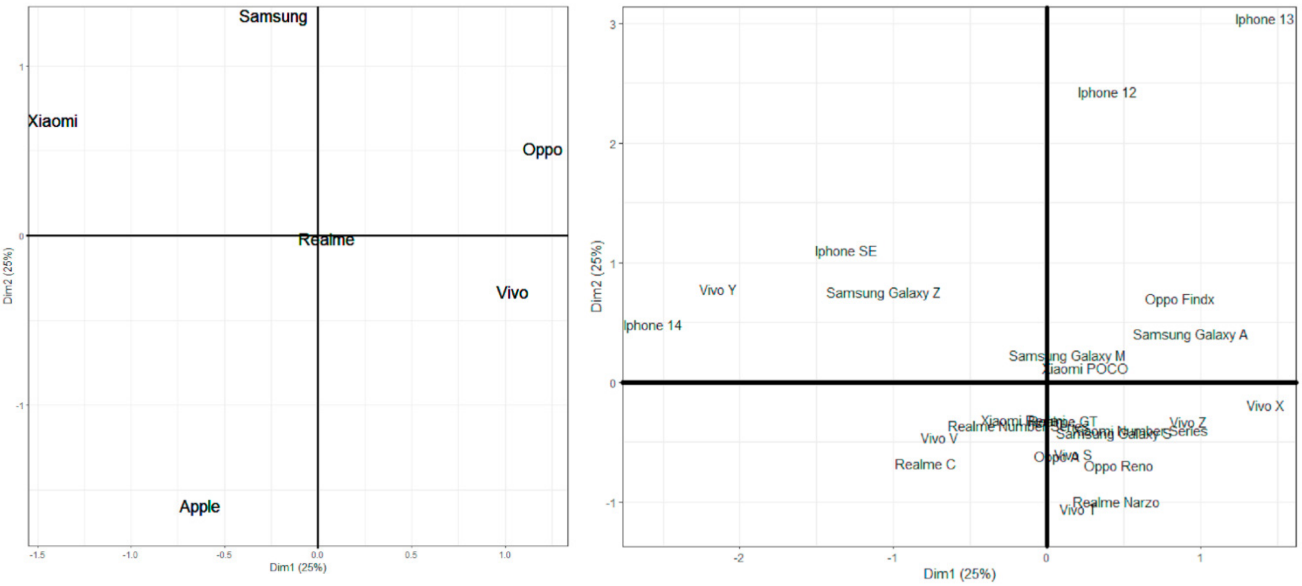

Figure 1 Perceptual Map (a) for Brand; (b) for Series

4.4. Clustering

After the perception maps being formed, the brand and series will be clustered based on their similarities to one another. Clustering is carried out as the final step to find out the formal brand and series positioning based on groups.

- Brands Clustering

This analysis uses a total of 3 clusters as only 6 brands were being analyzed. After determining the number of clusters, there are several ways and forms to visualize the clusters. Clustering will be visualized using dendrogram and cluster plots to clarify a grouping brand in each cluster as shown in Figure 2. From brand cluster in Figure 2, it can be seen that two of the three clusters have only one member. Those 2 clusters are Cluster 1 which is occupied by Apple and Cluster 3 which is occupied by Samsung. The other cluster, that is cluster 2 is occupied by other brands consisting Oppo, Realme, Vivo, and Xiaomi. It can be seen that Apple and Samsung form separate clusters and are far from each other. This result resonates with the brand perceptual positioning map in Figure 1a which also identifies Apple and Samsung as 2 brands that have quite a big difference between one another and other brands. As for other Android smartphone brands, such as Oppo, Realme, Vivo, and Xiaomi, they have gathered in one cluster which indicatesthat these four brands have close similarities to one another.

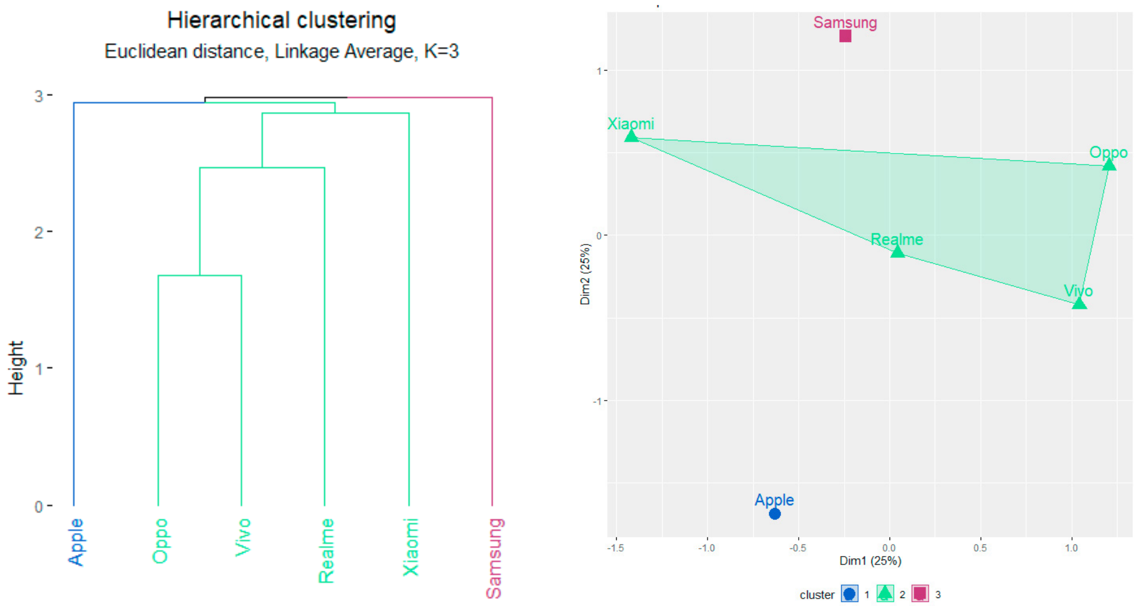

Figure 2 Brand Cluster (a) Dendrogram (b) Cluster Plot

- Series Clustering

Cluster visualization is carried out using dendrogram and cluster plots to facilitate understanding of smartphone series groupings as shown in Figure 3. From Figure 3, we know that the series was divided into 9 clusters. Cluster 1 is occupied by iPhone 12 Series. Cluster 2 is occupied by iPhone 13 Series. Cluster 3 is occupied by iPhone 14 Series. Cluster 4 is occupied by iPhone SE. Furthermore, Cluster 5 has the most members, consisting of Oppo A, Oppo Reno, Realme C, Realme GT, Realme Narzo, Realme Number Series, Samsung Galaxy M, Vivo S, Vivo T, Vivo V, Vivo Z, Xiaomi Poco, Xiaomi Redmi, and the Xiaomi Number Series. Cluster 6 has three members, consisting of Oppo Find X, Samsung Galaxy A, and Vivo X. Cluster 7 is only occupied by Samsung Galaxy S. Cluster 8 is only occupied by Samsung Galaxy Z. And finally, cluster 9 only has Vivo Y as a member of its cluster.

It can be seen that Apple has a differentiating value for each of its series. When we compare the Apple product series to other brands series, Apple is still different and tends to stand alone as a result of Apple's significant differentiating value. Vivo Y is able to stand alone and separate itself from other Vivo brand series. This might happen because Vivo Y has advantages or uniqueness which is a very big differentiating value offered to users when compared to other Vivo series which tend to gather in the same cluster. Samsung Galaxy S and Samsung Galaxy Z series also form a different cluster from other Samsung series. Furthermore, Samsung Galaxy S has a different cluster from Samsung Galaxy Z, which means that those 2 clusters have different characteristics and features.

4.5. Cluster Descriptions

The last stage in the analysis is identifying the clusters that are formed. This stage will help to find out the brand image that is formed in each cluster which is analyzed based on the LIWC output and factor from Principal Component Analysis.

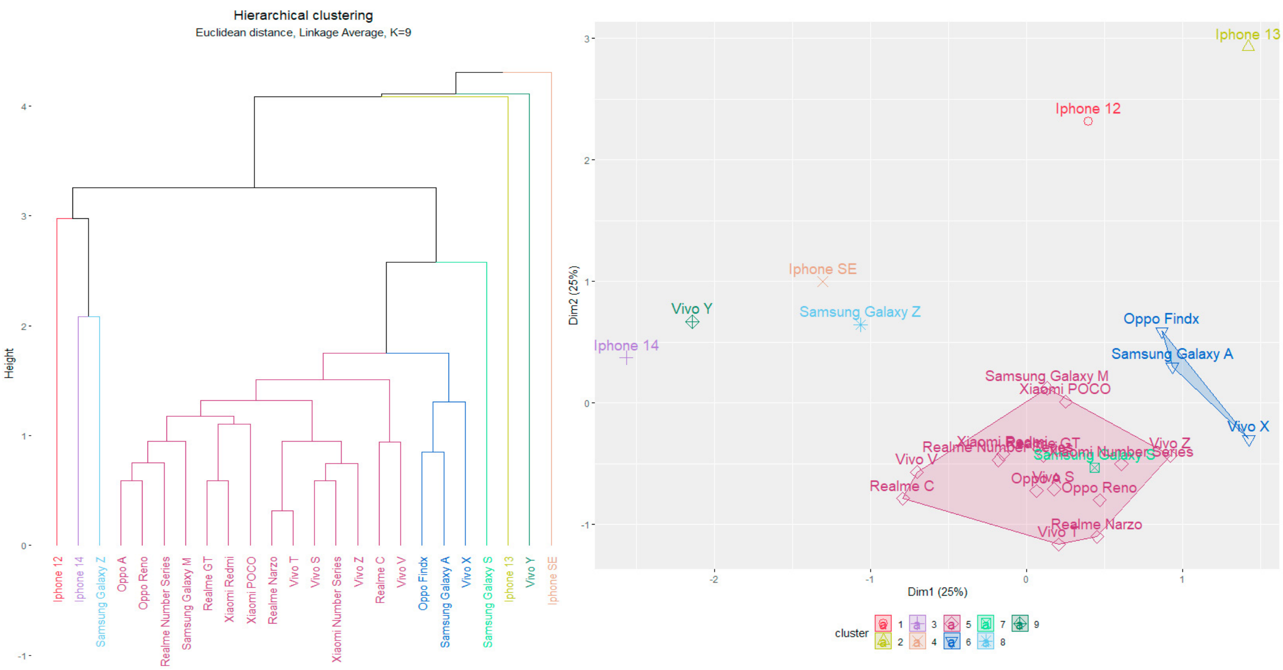

Figure 3 Series Cluster (a) Dendrogram (b) Cluster Plot

- Brands Cluster Description

To find out the brand image that is formed can be analyzed from the radar graph shown in Figure 4. For example, Cluster 1 which consists of Apple, tends to stand out on the 'Pride' factor shown in Figure 4a. This fact is related to variables that are associated with pride such as authentic, mental, and tone_neg. It is shown in Figure 4b that Cluster 1 has a high value on the authentic variable and a low value on the mental and tone_neg variables, which means Apple product has high authenticity, is less bad than other brands, and make their user less depressed than other brands. In conclusion, consumers who use Apple tend to have high pride regarding their high authenticity products which makes them less depressed and felt bad about the product. On the other hand, Cluster 3 which consists of Samsung brand stands out on the ‘Assurance & Quality’ factor. It is supported that Cluster 3 has a high value on the risk variable and a low value on the emo_anx variable as shown in Figure 4b. That information shows that Samsung brand has high security and protection so it makes their user less worried about the products. Cluster 3 also stands out on the ‘Inadequate’ factor that is associated with the fatigue and emo_neg variables which Samsung has a high value in those variables. This means that Samsung makes their user tired and bored. This fact shows that Samsung needs to improve its products. Cluster 2 which consists of Oppo, Realme, Vivo, and Xiaomi tends to stand out on the ‘user experience’ factor. This fact is supported by variables associated with the 'user experience’ factor which Cluster 2 has a high value of the visual, auditory, perception, leisure, and lifestyle variables as shown in Figure 4b. From that information, we know that brands in Cluster 2 have good user experience as they have good visual, auditory, and perception. Their products are also good for leisure and lifestyle.

- Series Cluster Description

Similar to the brand's cluster description, the series cluster description shown in Figure 5 can help to find out the image of the smartphone series. For series cluster description, we focused only on Cluster 1, 2, 3, 4, and 9 which have significant differences with the rest clusters. Figure 5b shows that Cluster 1, 2, 3, and 9 have low values on the ‘product imperfections’ factor. It is supported by a low value of the lack, fatigue, emo_anger, and tone_pos variables shown in Figure 5a. This fact means that Apple 12, Apple 13, Apple 14, and Vivo Y series have decent products as they have less imperfection in their products as their products are less lack and bad than other series and make their user less tired and frustrated. The difference between those clusters can be analyzed from other factors.

Clusters 2 and 9 which consist of Apple 13 series and Vivo Y series have superiority on 'user experience' as they have a high value on the achieve and leisure variables which means that the product in those series works better than other series and is good for leisure. Clusters 1, 2, and 3 that consists of Apple 12 series, Apple 13 series, and Apple 14 series have stand-out values on the 'consumer needs' factor and are supported with a low value of the want variables means that these series are less needed to improve as their user have less something they want to improve from the series. Cluster 3 which consists of Apple 14 series has stand-out values of the 'assurance & quality' factor. It is also supported by a low value of the emo_anx variable that shows that the users of this series have less worried about its products. It also shows that Cluster 4 which consist of Apple SE series did not stand out in all factor if we compare it with the other 4 Cluster. It means that Apple SE series is inferior in all aspects we analyze if we compare it with Apple 12, Apple 13, Apple 14, and Vivo Y series although it still has superiority with other series.

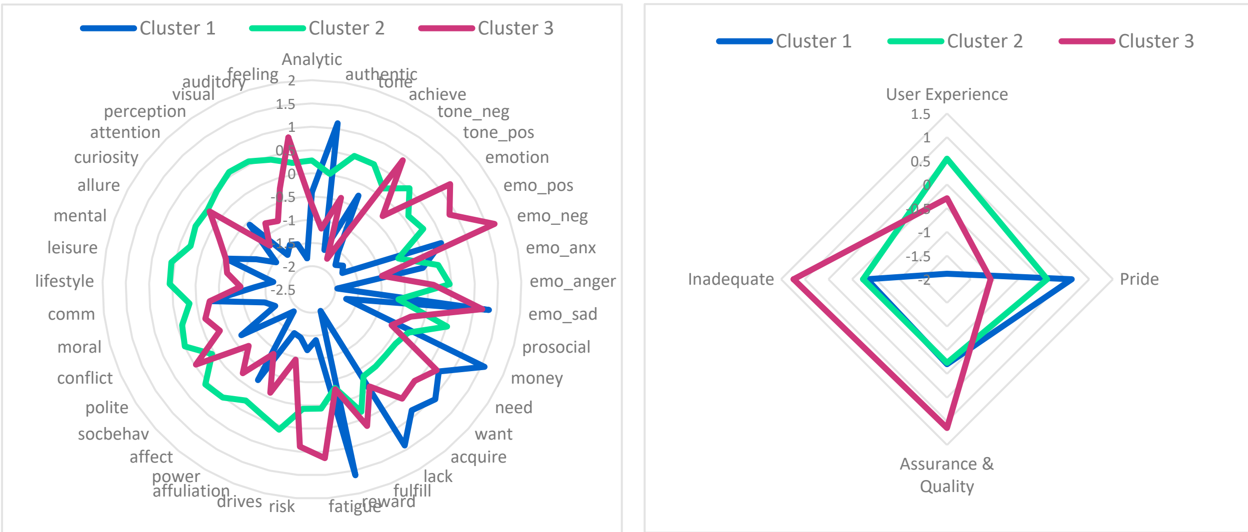

Figure 4 Brands Cluster Descriptions based on (a) LIWC output; (b) Factors

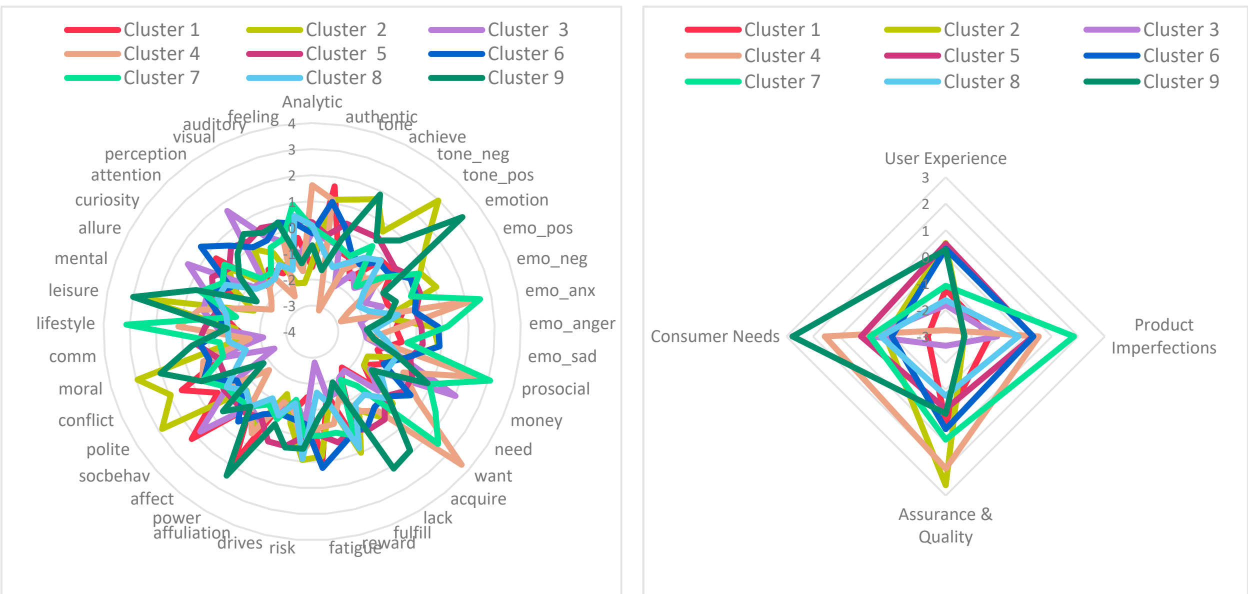

Figure 5 Series Cluster Descriptions based on (a) LIWC output; (b) Factors

5. Discussion

5.1. Contribution

This research contributes to add some insightful result and finding by analyzing brand position and brand image of smartphone especially for Indonesia market. The results of this study will also be useful as additional literature regarding the use of one lexicon-based approach for text mining, LIWC instead of machine learning approach as used in most previous research. The result of this analysis has similarity with research conducted by [3] which are the basic motivation of this research. Albeit the different object of analysis, this research resulted e know how This research produces information about the proximity of a brand to other brands based on 4 factors generated by conducting PCA on 41 selected LIWC variables. Although the result is different, research by [3] also generate information about the proximity of a brand to other brands. This research also generates information about brand cluster to identify whether a brand can be said to be significantly different from the others or still quite similar. The clustering results can be used as a benchmark to justify whether a brand serve the same or different segment with other brands based on the reviews. Information about clusters of brands was also generated in the research by [3]. The previous research which uses machine learning approach also generate information about the proximity of a brand to other brands but use different based to map the proximity as most of them use polarity or sentiment from reviews which was not carried out in this research [21, 23, 31, 34].

The brand image from this research is obtained from an interpretation based on the value of the existing factors of each brand. While the name of a factor is obtained by conducting in-depth discussions to find the right term to represent most of the variables associated with that factor. This also happened in research conducted by [3]. The steps to interpret the name of this factor is not carried out in research that uses a machine learning approach. In previous research which use machine learning approach, the brand image obtained from a list of topics that often appear and the associations of existing words with a particular topic [21, 23, 28, 31, 34]. Some of them use words correlation network to determine the topics [15, 28]. The topics generated from those researches tend to talk about physical attributes. The brand image generated in this research and research conducted by [3] were in the form of an emotional experiences and feeling after using the product rather than physical features which could be seen in Figure 4b that the factors are "user experience", "pride', "assurance & quality", and 'inadequate". In this research, extension analysis on sub-brands or series as a smaller part of the brand also carried out. This is different from research conducted [3] which analyzing the brands but not the sub-brands.

5.2. Practical Implications

The results of cluster analysis on the brand illustrated in Figure 2 show that Apple and Samsung are on the different clusters located far from each other. Those 2 brands also different from the other 4 brands which form 1 cluster in the middle as shown on Figure 2b. This shows that Apple and Samsung have obvious distinction if we compare with the other 4 brands. Obvious distinction shows that both brands have a strong differentiating image attached to them based on existing reviews. On the other hand, the other 4 brands seem do not have strong differentiating image attached to them as they grouped in the same cluster. Based on this analysis, Apple has strong pride image. It resonates with research conducted by [13] which finds that Apple brand is associated with eliteness and sophistication. Samsung has strong assurance and quality image. This result strengthens research results by [17] which find that Samsung have good quality product and have many service centers that make consumer feel secure to have Samsung product. The distinctive and strong image is a great starting point for a smartphone brand as strong image make strong impression in potential consumer mind [6]. Strong brand image and personality could affect purchase intention of potential consumer [27]. Strong brand image has proven to have a positive impact on Apple and Samsung by making these two brands lead the global smartphone brand and the only two smartphone brand that are included as top 10 global brand ranking in 2023 [9, 16]. From that explanation, we can argue that, if a brand wants to gain advantage and strengthen their market, the brand needs to construct a good, strong, and distinctive emotional values [27]. However, a strong and distinctive value alone is not enough to gain good position in market, a strong brand communication through several method including advertising is also important to smartphone brands.

If we do a deep analysis on series positioning and image, we know that 7 of 24 existing series from 6 brands have their own segment as they have their own cluster. From Figure 3b we know that all of existing Apple series have their own cluster. This means that each Apple series have their own values based on the reviews. That fact means that the value of released iPhone products is different for each different release time. This fact resonates with the finding of [13] research that Apple always provide unique innovations in each of its products. The strong distinctive value for each of its products make Apple have successful sales in all of its product release [36]. For Samsung, only 2 series that have own cluster, that are Samsung Galaxy S and Samsung Galaxy Z. Although Samsung Galaxy S located near cluster 5 that have most cluster member or we can say general positioning, this series still have distinctive value. The newest Samsung Galaxy Z series which consist of foldable screen products have own segment and located near Apple series. The newest Galaxy Z value is breakthrough innovation as their products use unconventional foldable screen which the result of breakthrough innovation. The strong value of Samsung Galaxy S and Galaxy Z also proved to have positive impact on their sales [22, 38]. Last but not least, Vivo Y series also have their own segment which is different from most of the series from non-Samsung Android brands. This distinction also has positive impact on Vivo Y series as this series dominate the sales of Vivo [5].

5.3. Limitation and Future Research

This research only uses LIWC as a established list of word dictionary tools which use psychological process rather than actual topics derived from the review, so it is necessary to carry out further interpretation of the analysis results. Besides that, in this study, the position of a brand is only based on proximity based on LIWC results, so it does not know the positives and negatives of brand positioning, so it cannot be concluded with certainty which one is better, only determines which brand has a strong association with other brands, which one is different with the others. The generated brand image is only based on the strength of the association of a brand with certain factors. If the value of certain factors is low for a brand, it means that the brand does not have a strong association with that particular topic, does not determine whether the brand good or bad. This study use lexicon-based approach and expert review only. Comparing the result of analysis from two different approach, lexicon-based and machine learning-based is not conducted in this research. So, we can not determine which approach generates more relevant result of analysis. Besides that, comparing the result of brand positioning and brand image extraction from user reviews and expert review also not conducted in this research.

From explanation of limitations of this research, we recommend to do analysis which includes elements to assess sentiment from reviews to see how the brand is positioned based on their quality to determine which brand is superior than the other. We also recommend to do analysis that use both lexicon-based and machine learning-based approach to compare the relevancy of each approach to extract brand positioning and brand image from reviews. In the last, we recommend to do analysis that use both user reviews and expert reviews as database for the analysis to extract brand positioning and brand image to compare the result of analysis based on expert opinion and user emotional experience, whether the result contradicting or supporting each other.

6. Conclusion

This research uses the text mining method utilizing the LIWC tool to analyze Brand Positioning and Brand Image of Smartphones in Indonesia based on online expert reviews. The analysis of brand positioning shows that Apple and Samsung tend to stay away and occupies cluster that is quite far away compared to other brands. This may occur when Apple and Samsung may have significant uniqueness and differentiating value compared to other brands. From the brand cluster description, we know that Apple stands out on the 'Pride' factor which means owning Apple products makes someone proud. It can be caused because many people felt that Apple products have high authenticity than other brands. On the other hand, Samsung stands out on the 'Assurance & Quality' and 'Inadequate' factors which means owning Samsung products makes someone less worried as they felt that Samsung products have high security and protection but they want Samsung to improve its products as they felt that Samsung products are quite boring. The rest of the Android Brands are stands out on the 'User Experience' factor which means their user felt their product have a good user experience as they have good visual, auditory, and perception. From the analysis of series positioning, Apple product series is always located at the outermost point and far away from other brand's series. For Samsung brand, Samsung Galaxy S and Samsung Galaxy Z have their own segments. Only Vivo Y series from the non-Samsung Android-based brands separated from most of other brand series and offset Apple's position. Apple and Vivo Y tend to be far away and separate from other brands because both Apple and Vivo Y have significant differentiating values and have a strong positive image for their users. So, they cannot be combined or compared with other brands. In general, the perceptual maps and clusters that are created based on brands and series tend to be in harmony with each other, however, on some occasions, the series has a special perception and positioning if we compare it with the general perception of a brand.

Appendix A. LIWC Output

A.1.Descriptive Statistics of LIWC Result for Brands

LIWC Variable	Number of Brands	Min	Max	Mean	Std. Dev
Analytic	6	82.66	87.61	84.4790	1.74544
Authentic	6	19.45	23.83	21.6963	1.90935
Tone	6	50.64	57.38	54.2050	2.21464
achieve	6	0.92	1.05	0.9982	0.04663
tone_neg	6	0.26	0.31	0.2955	0.02095
tone_pos	6	2.25	2.68	2.5020	0.14488
emotion	6	0.49	0.64	0.5770	0.05317
emo_pos	6	0.32	0.47	0.4136	0.05367
emo_neg	6	0.11	0.14	0.1203	0.01030
emo_anx	6	0.03	0.05	0.0378	0.00856
emo_anger	6	0.01	0.02	0.0177	0.00536
emo_sad	6	0.01	0.05	0.0272	0.01350
prosocial	6	0.48	0.78	0.6606	0.10464
money	6	0.59	0.76	0.6631	0.06265
need	6	0.21	0.35	0.2965	0.05488
want	6	0.08	0.14	0.1182	0.02414
acquire	6	0.37	0.42	0.3986	0.02009
lack	6	0.10	0.18	0.1432	0.02345
fulfil	6	0.18	0.40	0.3474	0.08543
reward	6	0.11	0.22	0.1528	0.04368
fatigue	6	0.01	0.01	0.0098	0.00185
risk	6	0.13	0.21	0.1708	0.03115
Drives	6	1.88	2.23	2.0887	0.14595
affiliation	6	0.33	0.52	0.4364	0.06841
power	6	0.73	0.95	0.8348	0.08893
Affect	6	2.55	3.00	2.8435	0.15397
socbehav	6	1.75	2.19	2.0108	0.16314
polite	6	0.07	0.12	0.0989	0.01782
conflict	6	0.01	0.05	0.0339	0.01504
moral	6	0.06	0.08	0.0740	0.00787
comm	6	0.55	0.74	0.6458	0.06261
Lifestyle	6	2.35	3.11	2.7626	0.32557
leisure	6	0.32	0.98	0.7255	0.24563
mental	6	0.00	0.00	0.0004	0.00071
allure	6	3.76	4.64	4.0935	0.29427
curiosity	6	0.19	0.24	0.2185	0.01539
attention	6	0.34	0.42	0.3751	0.02937
Perception	6	8.07	10.12	9.2678	0.75294
visual	6	1.65	2.34	2.0047	0.24682
auditory	6	0.12	0.26	0.1951	0.05356
feeling	6	0.34	0.64	0.5486	0.11303

A.2.Descriptive Statistics of LIWC Result for Series

LIWC Variable	Number of Series	Min	Max	Mean	Std. Dev
Analytic	24	80.79	88.82	84.6538	2.53740
Authentic	24	16.61	29.19	21.5025	3.02485
Tone	24	39.70	60.91	54.1208	4.57533
achieve	24	0.76	1.44	1.0054	0.14569
tone_pos	24	1.77	2.92	2.4992	0.25847
tone_neg	24	0.16	0.47	0.2983	0.06735
emotion	24	0.36	0.74	0.5792	0.11084
emo_pos	24	0.22	0.58	0.4142	0.10232
emo_neg	24	0.05	0.29	0.1225	0.05391
emo_anx	24	0.01	0.09	0.0383	0.01736
emo_anger	24	0.00	0.04	0.0175	0.01225
emo_sad	24	0.00	0.15	0.0288	0.03301
prosocial	24	0.37	0.97	0.6596	0.14648
money	24	0.41	1.08	0.6521	0.17764
need	24	0.11	0.51	0.2900	0.10009
want	24	0.04	0.24	0.1158	0.04262
acquire	24	0.26	0.52	0.4033	0.05910
lack	24	0.07	0.29	0.1433	0.05105
fulfil	24	0.13	0.58	0.3442	0.10333
reward	24	0.06	0.45	0.1546	0.09785
fatigue	24	0.00	0.04	0.0104	0.00955
risk	24	0.05	0.25	0.1629	0.05103
Drives	24	1.50	2.63	2.0942	0.28778
affiliation	24	0.23	0.70	0.4358	0.13619
power	24	0.54	1.45	0.8321	0.18955
Affect	24	2.21	3.26	2.8413	0.26089
socbehav	24	1.48	2.47	2.0117	0.23894
polite	24	0.04	0.16	0.0983	0.03116
conflict	24	0.00	0.09	0.0363	0.02318
moral	24	0.00	0.11	0.0758	0.02552
comm	24	0.42	0.83	0.6433	0.11816
Lifestyle	24	2.12	4.44	2.8029	0.51946
leisure	24	0.19	2.15	0.7654	0.40474
mental	24	0.00	0.01	0.0004	0.00204
allure	24	3.17	5.59	4.0592	0.43883
curiosity	24	0.08	0.35	0.2179	0.06372
attention	24	0.24	0.54	0.3700	0.08496
Perception	24	7.96	10.62	9.2338	0.78162
visual	24	1.21	2.53	1.9783	0.30938
auditory	24	0.03	0.37	0.1867	0.07441
feeling	24	0.21	0.84	0.5429	0.15898

Appendix B. Principal Component Analysis

B.1. Principal Component for Brands

Variable	Factor Loadings				PC Name
	PC1	PC2	PC 2	PC 4	
affect	0.988	-0.059	0.020	0.060	User Experience
tone_pos	0.977	0.082	0.003	0.090	
emo_anger	0.972	-0.024	0.113	0.169	
perception	0.948	0.146	-0.203	-0.032	
socbehav	0.942	0.308	-0.088	0.002	
tone	0.942	0.240	-0.010	0.135	
visual	0.912	0.245	-0.110	-0.095	
drives	0.884	0.317	-0.139	-0.210	
prosocial	0.878	-0.080	0.089	-0.275	
fulfill	0.874	-0.262	0.210	0.269	
leisure	0.860	-0.127	-0.355	-0.170	
emo_sad	-0.837	-0.018	0.354	0.377	
auditory	0.830	0.072	0.446	-0.303	
moral	0.828	0.428	0.262	0.188	
conflict	0.799	-0.179	-0.008	-0.338	
emo_pos	0.790	-0.092	0.375	0.473	
allure	0.738	0.356	0.236	0.190	
reward	-0.716	0.574	-0.146	0.148	
feeling	0.716	-0.652	0.248	0.016	
money	-0.695	-0.076	-0.046	-0.604	
lifestyle	0.688	-0.164	-0.562	-0.312	
curiosity	0.673	-0.466	-0.369	0.363	
emotion	0.665	-0.242	0.422	0.564	
affuliation	0.633	-0.561	-0.106	-0.407	
want	-0.625	-0.427	0.383	-0.438	
lack	-0.616	0.438	-0.317	0.525	
power	0.368	0.881	0.062	0.015	Pride
tone_neg	0.504	-0.835	0.175	-0.076	
comm	0.336	0.783	0.492	0.037	
authentic	-0.233	0.755	0.198	-0.441	
mental	0.512	0.746	0.115	0.299	
attention	0.604	0.735	0.080	-0.205	
achieve	0.452	0.687	-0.472	-0.305	
polite	0.243	-0.584	0.516	-0.473	
emo_anx	0.113	-0.254	-0.897	-0.070	Assurance & Quality
Analytic	0.267	-0.179	-0.842	0.222	
need	-0.457	0.042	0.787	-0.304	
risk	0.542	-0.135	0.656	0.230	
emo_neg	-0.504	-0.360	0.158	0.769	Inadequate
acquire	-0.490	0.383	-0.102	0.658	
fatigue	0.450	-0.587	-0.164	0.648	

B.2. Principal Component for Series

Variable	Factor Loadings				PC Name
	PC1	PC2	PC 2	PC 4	
tone_pos	0.875	0.112	0.069	-0.155	User Experience
Tone	0.873	-0.080	-0.041	-0.192	
Affect	0.820	0.301	0.174	-0.147	
emo_pos	0.725	0.206	0.233	-0.421	
Drives	0.698	-0.376	0.186	0.285	
Perception	0.694	0.268	-0.234	0.181	
visual	0.682	0.077	-0.424	0.104	
fulfill	0.652	0.163	-0.158	0.204	
prosocial	0.605	-0.058	0.037	0.479	
achieve	0.558	-0.504	0.376	-0.008	
emo_sad	-0.558	0.270	0.514	0.350	
Lifestyle	0.528	0.148	0.028	0.371	
leisure	0.507	0.398	-0.130	0.237	
emotion	0.498	0.469	0.394	-0.326	
allure	0.450	-0.016	0.127	-0.355	
affiliation	0.404	-0.025	-0.027	0.221	
attention	0.401	-0.362	-0.366	0.175	
auditory	0.391	0.247	-0.281	0.177	
mental	0.228	0.167	-0.037	-0.127	
emo_anger	0.130	0.823	0.161	0.137	Product Imperfection
reward	0.147	-0.783	0.323	0.383	
tone_neg	-0.246	0.722	0.455	0.177	
conflict	0.425	0.673	0.147	0.057	
fatigue	-0.204	0.628	0.189	0.324	
lack	0.135	-0.609	0.395	0.272	
emo_neg	-0.399	0.576	0.402	0.330	
power	0.440	-0.574	0.190	0.410	
money	-0.128	-0.573	0.042	0.165	
feeling	0.221	0.555	-0.404	-0.302	
Analytic	-0.201	0.494	-0.020	0.435	
acquire	0.176	-0.206	0.774	-0.113	Assurance & Quality
moral	0.386	0.192	0.631	-0.277	
emo_anx	-0.210	0.256	-0.502	0.493	
curiosity	0.292	0.138	-0.501	-0.163	
need	0.057	-0.434	-0.457	-0.287	
risk	0.175	-0.100	-0.419	-0.108	
socbehav	0.573	-0.037	0.187	0.671	Consumer Need
polite	0.219	0.100	0.127	-0.540	
Authentic	-0.145	-0.100	0.411	-0.475	
want	0.074	-0.185	0.254	-0.407	
comm	0.082	-0.160	0.197	0.339	

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